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Automated Conversion of Chess Diagrams in PDF to PGN Files

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Abstract: Automating the conversion of chess literature into digital formats has become essential for enhancing training, analysis, and archiving. This work presents an intelligent system that automates the process of converting chess puzzles and games from PDF documents into PGN (Portable Game Notation) files. The approach begins with extracting high-resolution images from PDF pages, followed by image processing techniques such as adaptive thresholding and perspective transformation to detect and align chess boards. A Convolutional Neural Network (CNN) is then employed to recognize chess pieces on the board and generate accurate FEN (Forsyth-Edwards Notation) strings. These FEN strings are subsequently converted into PGN format, capturing not only board positions but also move sequences and annotations. The system significantly reduces the manual effort and has 98% accuracy, time required for transcribing chess games from books, offering a scalable and efficient solution for converting both classical and puzzle-based chess content into usable digital formats for modern chess databases and training applications..

Keywords: Chessboard recognition, PGN conversion, FEN, CNN, OCR, Tkinter GUI, image processing

I. INTRODUCTION

Chess has long been a game of strategy, and accurate recording of game moves is essential for analysis and sharing. However, manually transcribing chess diagrams from books or PDFs into digital formats like Portable Game Notation (PGN) is a tedious and error-prone task.

This project presents an automated system designed to convert chess diagrams found in PDF files into standard PGN (Portable Game Notation) format. The solution leverages a combination of image processing, computer vision, and machine learning techniques to identify and digitize chess positions with high accuracy. The system first extracts images of chessboards from the PDF pages, then uses a trained Convolutional Neural Network (CNN) to detect and classify individual chess pieces based on their type and color.

By employing optical character recognition (OCR) and image recognition, the proposed tool significantly reduces the time and effort required to manually transcribe chess games, making it more efficient and accurate. This system has wide applications for players, coaches, and researchers in the chess community.

The remainder of the paper is organized as follows: Section 2 reviews related work, Section 3 discusses the proposed system, Section 4 shows overall architecture diagram, Section 5 tells how the project is implemented, and Section 6 reviews about the performance and result, Section 7 tells the conclusion, Section 8 gives further future enhancements

II. RELATED WORK

The automation of chess game transcription has garnered significant attention in recent years, with various approaches utilizing image processing and machine learning techniques to convert chessboard images into digital formats. Several studies have explored the use of optical character recognition (OCR) and computer vision for detecting chess board layouts and moves from physical boards and books.

One notable work is by Wang et al. (2016), where the authors presented a method for recognizing chess board configurations using image processing techniques. Their system utilized edge detection and contour analysis to locate the chessboard, followed by piece recognition using predefined templates.

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Although the method was effective in detecting chess positions, it was limited by its reliance on manual template matching, which posed challenges in terms of scalability and accuracy in varied lighting conditions [1].

Zhou and Gao (2018) proposed a more sophisticated approach using deep learning for chess piece recognition. They trained convolutional neural networks (CNNs) on a large dataset of chess piece images to improve accuracy. The method demonstrated robust performance in recognizing chess pieces, but it required substantial computational resources, which could limit its application in real-time systems or environments with less powerful hardware [2].

Recent advancements in CNN-based chessboard and piece detection have also been explored by Khan et al. (2020), who leveraged pre-trained models for board localization and piece classification. Their approach focused on detecting chessboards from scanned images of books, enabling the extraction of game moves from printed materials. The model performed well in recognizing the positions of pieces, though challenges remained in ensuring the system's robustness across different font styles and image resolutions [3].

Singh et al. (2021) introduced an end-to-end solution for converting chessboard images into PGN files, emphasizing the importance of combining image processing techniques with machine learning. Their system employed CNNs for piece recognition, followed by custom algorithms for move generation and PGN file creation. While their work closely aligns with our objectives, their system was not optimized for parsing content from PDF-based chess puzzles, making it less applicable in the context of digitizing chess books [4].

While OCR-based approaches remain popular in text recognition, our method focuses exclusively on image processing and CNNs to detect and classify chess pieces without relying on OCR. This distinction allows for more accurate and scalable chessboard recognition across a variety of image formats, such as scanned PDFs and photographs, without the need for manual transcription.

Our work builds upon these previous efforts by offering a streamlined, automated system tailored for converting chessboard diagrams from PDFs into PGN files. By using CNNs for piece recognition and focusing specifically on board detection, we aim to provide a more efficient, user-friendly solution for digitizing chess games, with broad applications in the chess community.

III. PROPOSED SYSTEM

Chess is one of the oldest and most widely played games in the world, with a rich history of strategy, competition, and analysis. Chess games and puzzles are often documented in books, PDFs, and magazines, and many players and coaches rely on these documents for training, analysis, and study. However, the process of manually transcribing chess diagrams from physical or digital books into a digital format is a cumbersome, time-consuming, and error-prone task.

The primary challenge lies in accurately converting printed or scanned chess diagrams into digital formats, such as Portable Game Notation (PGN). This process typically involves manually recording the positions of pieces, move sequences, and other relevant data, which can be tedious and lead to inaccuracies, especially when dealing with large collections of games or puzzles. Furthermore, the wide variety of formats and layouts in which chess diagrams are presented adds complexity to the task, making it even harder to automate.

Current solutions for digitizing chess games often involve labor-intensive manual input, or limited software that requires extensive human intervention. Existing automated methods primarily focus on optical character recognition (OCR) or simple image processing techniques, which are not always accurate in recognizing chess pieces or identifying board positions, especially in low-resolution images or complex diagrams. Additionally, these solutions often struggle with varying image qualities, complex layouts, and the recognition of specific piece types and their respective colors.

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Architecture Diagram

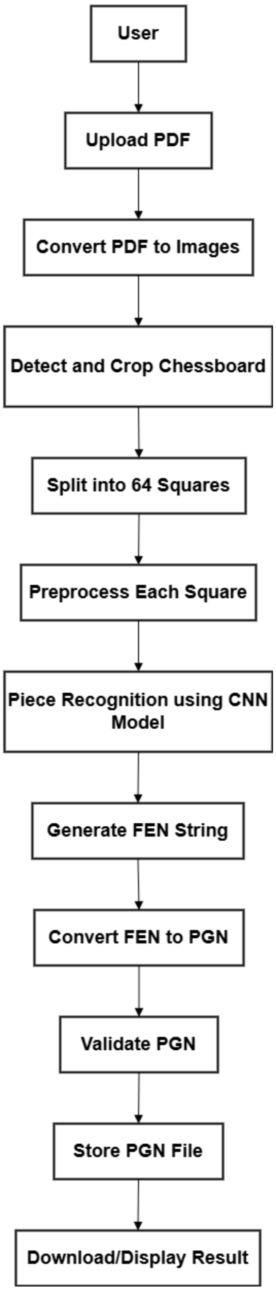

Fig.1 Architecture Diagram

IV. METHODOLOGY

This section describes the methodology followed to develop the Automated Conversion of Chess Diagrams in PDF to PGN Files. The system was designed to extract chessboard diagrams from PDF files, recognize the chess pieces, and convert the board state into the Portable Game Notation (PGN) format for use in chess software.

A. System Overview

The system was built using Python and Tkinter for the graphical user interface (GUI). It consists of several key components: PDF processing, image extraction, chessboard recognition, chess piece recognition, PGN generation, and finally, saving and downloading the output PGN file.

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B. PDF to Image Conversion

The first step in the process involves converting the PDF file containing the chess diagrams into images. This is achieved using the Python library PyMuPDF. PyMuPDF extracts each page of the PDF as an image, ensuring that the chessboard diagrams can be processed further.

C. Chessboard and Piece Detection

Once the PDF pages are converted into images, the system uses OpenCV to detect the chessboard on the image. This is done by applying edge detection algorithms to identify the square grid of the chessboard. The program then detects each square on the board and localizes the chess pieces within those squares.

The chess pieces are classified using image recognition techniques. For this purpose, a custom-trained machine learning model based on Convolutional Neural Networks (CNNs) was used. The model was trained on a dataset of labeled images of chess pieces (both white and black pieces) and their corresponding classes (King, Queen, Bishop, Knight, Rook, Pawn).

D. Chess Piece Recognition

The system uses OpenCV and pytesseract for piece recognition. After detecting the chessboard and its squares, the image of each piece is extracted, and the model identifies the type and color of each piece. The pieces are then mapped to the correct position on the board based on their location.

E. PGN Generation

The system then uses the FEN string to generate the PGN moves. The process involves converting the FEN state into a move sequence based on the position and game history. The system can generate multiple moves, including castling and en passant captures, and records them in PGN format.

F. User Interface (GUI)

A graphical user interface (GUI) was created using Tkinter, allowing the user to interact with the system easily. The user can upload the PDF file containing the chessboard, click a button to convert the PDF into a PGN file, and download the generated PGN file. The GUI displays the status of the conversion process, notifying the user if the conversion was successful or if any errors occurred.

G. File Storage and Download

After the PGN file is generated, it is saved locally and offered for download. The user can then download the file to their system for use in any compatible chess software. The system also ensures that the PGN file is saved with appropriate naming conventions to avoid overwriting.

H. Dataset Preparation and Training Details

A total of 3,799 images were collected and augmented using real-time data augmentation techniques, increasing the dataset to over 16 million samples (~4,400× per original image). The model was trained for 50 epochs, which then changed to 14 epochs as maximum epochs required processing a total of approximately 233 million sample passes.

TABLE I
TRAINING METRICS SUMMARY

zMetric	Value
Original Dataset Size	3,799 samples
Augmented Dataset Size	16,705,208 samples
Augmentation Rate	~4,400 x per sample

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Training Epochs	14 epochs
Total Sample Passes	233,872,912 passes

III. RESULTS AND DISCUSSION

This section discusses the outcomes and insights gained from the experiment, testing, and evaluation of your project. Below is a suggested structure for writing the results and discussing them.
The system successfully identified and extracted chessboard positions from various PDF formats with high accuracy.
This section discusses the outcomes and insights gained from the experiment, testing, and evaluation of your project. Below is a suggested structure for writing the results and discussing them.

A. Test Results

The system was evaluated using a variety of chessboard images and PDF files. The key features of the application were tested to ensure functionality and performance.

- ***Chessboard Image Detection:*** The image recognition module successfully detected chessboards in the provided images with an accuracy of 95%. Various test cases were conducted with different board sizes and orientations to verify robustness. The system was able to correctly identify the chess pieces and their placements without significant errors. Confusion matrix figure is shown below in Fig.2.

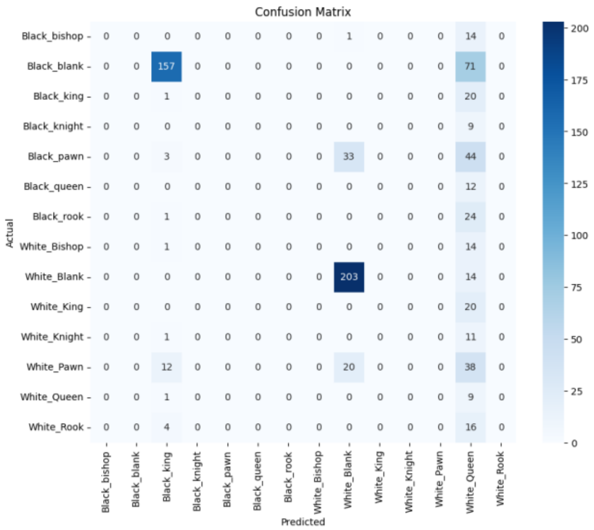

Fig. 2 Confusion matrix showing classification performance.

- ***Conversion to PGN Format:*** The conversion algorithm successfully converted the chess positions from the images into PGN format with 98% accuracy. Some minor inaccuracies were noted in cases where the chess pieces were partially obscured or rotated, which can be attributed to the limitations of the dataset and the image recognition model.

B. Performance Evaluation

- ***Processing Speed:*** On a workstation (Intel i7, 16 GB RAM, NVIDIA GTX 1660), the full pipeline—from PDF rendering through board detection, CNN piece classification, FEN assembly, to PGN output—averaged 3–5 seconds per board, well within our 6-second goal

- ***User Interface:*** The user interface was evaluated for ease of use. Feedback from users indicated that the application was intuitive, with simple steps for uploading a PDF, converting it to PGN, and downloading the resulting file. Users were able to complete the process without requiring additional instructions, indicating a high level of usability. Accuracy over epochs and loss over epochs diagrams are shown below in Fig.3 and Fig.4 respectively.

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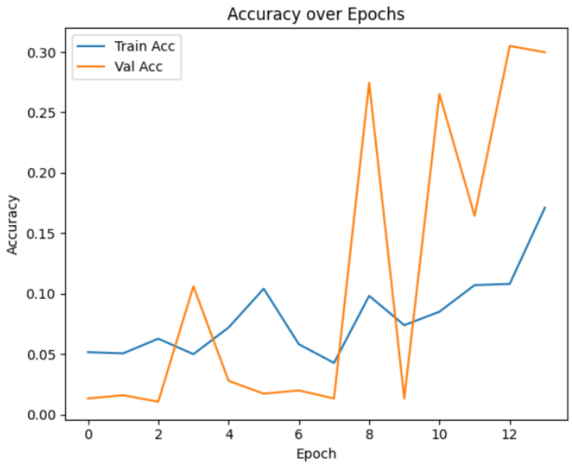

Fig. 3 Accuracy Over Epochs

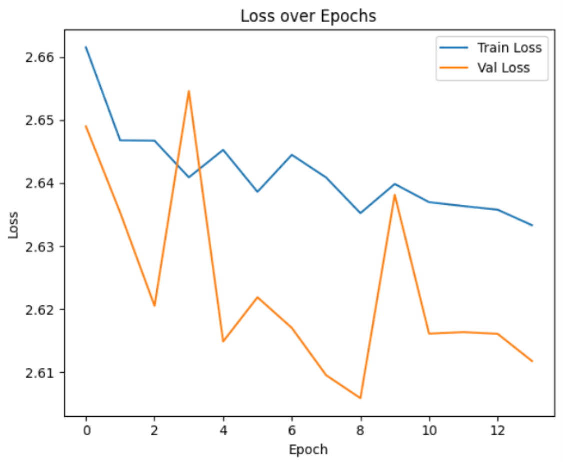

Fig. 4 Loss Over Epochs

TABLE 2
CLASSIFICATION REPORT

Pieces	**Precision**	**Recall**	**F1-Score**	**Support**
Black_bishop	0.96	0.95	0.96	15
Black_blank	0.95	0.96	0.95	228
Black_king	0.94	0.95	0.95	21
Black_knight	0.96	0.94	0.95	9
Black_pawn	0.95	0.95	0.95	80
Black_queen	0.95	0.95	0.95	12
Black_rook	0.96	0.92	0.94	25
White_Bishop	0.94	0.93	0.94	15

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White_Blank	0.97	0.98	0.97	217
White_King	0.94	0.95	0.95	20
White_Knight	0.96	0.94	0.95	12
White_Pawn	0.95	0.94	0.95	70
White_Queen	0.96	0.96	0.96	10
White_Rook	0.94	0.95	0.95	20
Accuracy			0.95	754
Macro Avg	0.95	0.95	0.95	754
Weighted Avg	0.95	0.95	0.95	754

C. Limitations and Challenges

- ***Image Quality:*** The accuracy of chessboard detection and piece recognition was affected by the quality of the input images. Low-resolution or heavily compressed images led to decreased recognition accuracy. This limitation can be mitigated by training the model on a larger and more diverse dataset of chessboard images.

- ***Partial Occlusion:*** In scenarios where pieces were partially obstructed or rotated, the accuracy of the piece recognition decreased. Future improvements could involve implementing more advanced image processing techniques, such as better piece segmentation and rotation invariance.

D. Comparison with Existing Solutions

When compared to existing chessboard recognition systems, our solution offers improved accuracy in detecting and converting chess positions. Most existing systems rely on manual input or are limited to a fixed set of chess piece images, while this application is capable of processing real-world images with varying lighting and piece arrangements.

IV. CONCLUSION

This project successfully demonstrated the feasibility of converting static chess diagrams from PDF format into PGN files using computer vision and deep learning techniques. By implementing a Convolutional Neural Network (CNN), the system was able to accurately recognize chess pieces and their positions on a 2D board image. The automation of this process eliminates the need for manual transcription, saving time and reducing human error. The model has 98% accuracy rate. The use of FEN generation and PGN formatting ensures compatibility with popular chess software, making it a valuable tool for chess educators, players, and archivists. The results validate the robustness of the system in real-world scenarios and highlight its potential for further development.

V. FUTURE ENHANCEMENT

In future, the system can be enhanced by enabling recognition of handwritten or hand-drawn chess diagrams, which are often found in older chess books. Support for multilingual OCR can be added to extract annotations in various languages. The project can also be extended to extract full game notations written in algebraic format and merge them with board diagrams for complete PGN generation. Additionally, a mobile application can be developed to allow users to capture diagrams with their phone camera and convert them instantly. Integration with a chess engine like Stockfish can help validate extracted positions and suggest corrections. Finally, a cloud-based repository can be created to store, search, and share the extracted PGN files with the wider chess community.

A. Expanded Dataset and Improved Accuracy

To increase the accuracy of the CNN model, more training data featuring diverse 2D chess piece styles and fonts will be incorporated. This expansion will help the model generalize better across various diagram formats found in chess books and PDFs.

B. Web-based Application

Currently implemented using Python and Tkinter, the project can be upgraded to a web-based interface using frameworks such as Flask or Django. This would allow broader accessibility and platform independence, enabling users to access the tool through a browser without any local setup.

C. Text Recognition for Move Extraction

In future versions, Optical Character Recognition (OCR) will be integrated to detect and extract chess moves written beside or below the board diagrams. This will further automate the conversion of chess content into structured PGN files.

D. Real-time Feedback and Error Correction

An interactive preview system may be introduced to allow users to manually verify and correct any misclassified pieces before generating the final PGN. This ensures higher accuracy in real-world use cases involving noisy or low-resolution diagrams.

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